Inverted-U relationship between innovation and survival: Evidence from firm-level UK data

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Abstract

Theoretical and empirical work on innovation and firm survival has produced varied and often conflicting findings. In this paper, we draw on Schumpeterian models of competition and innovation and stochastic models of firm dynamics to demonstrate that the conflicting findings may be due to linear specifications of the innovation-survival relationship. We demonstrate that a quadratic specification is appropriate theoretically and fits the data well. Our findings from an unbalanced panel of 39,705 UK firms from 1997-2012 indicate that an inverted-U relationship holds for different types of R&D expenditures and sources of funding. We also report that R&D intensity is more likely to increase survival when firms are in more concentrated industries and in Pavitt technology classes consisting of specialized suppliers of technology and scale-intensive industries. Finally, we report that the effects of firm and industry characteristics as well as macroeconomic environment indicators are all consistent with prior findings. The results are robust to step-wise modeling, controlling for left truncation and use of lagged values to address potential simultaneity bias.

Keywords: innovation; post-entry performance; R&D; survival analysis
JEL classification: C41, D21, D22, L1, 03

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1. Introduction

The theoretical and empirical work on firm dynamics has produced a wide range of findings on entry and exit patterns. The most often-cited empirical patterns include the following: (i) entry and exit rates are highly and positively correlated across industries; (ii) high entry rates are often associated with high rates of innovation and increased efficiency; (iii) firm size and age are correlated positively with survival; (iv) small firms that survive tend to grow faster than larger firms; and (v) younger firms have a higher probability of exiting, but those that survive tend to grow faster than older firms (Geroski, 1995; Klette and Kortum, 2004).

Nevertheless, the evidence on how innovation affects firm entry and exit remained mixed. Early theoretical models adopt a stochastic approach, in which firm- or industry-specific factors (including innovation) have no role in determining firm survival. Entry and exit decisions are made through passive learning about the effect of the idiosyncratic shocks on firm value (Jovanovic, 1982; 1994). In Hopenhayn (1992), survival depends on firm-specific productivity shocks and some industry characteristics such as entry cost and production technology; but innovation is not modelled as a particular source of productivity shock. Ericson and Pakes (1995) is the first study where innovation plays a central role in determining firm performance, including entry and exit. In this second-generation stochastic model, firms decide to remain or exit after discovering how innovation affects firm value. Because innovation is risky and associated with high levels of return uncertainty, the model predicts a negative relationship between innovation and firm survival.

As a third strand in the theoretical effort, evolutionary models emphasize the importance of 'innovation regimes' that mediate the effect of innovation on survival. In entrepreneurial regimes, higher levels of innovation are associated with higher survival rates because innovation is generally undertaken by small/innovative firms that break into the market and survive. In contrast, when the innovation regime is routinized – i.e., when it is dominated by large incumbent firms - innovation is associated with lower survival rates. Nevertheless, Aghion et al (2013) demonstrate that the differential effects of innovation on productivity (and hence survival) may be driven by relative positions of the firms *vis-à-vis* the technology frontier rather than by the dichotomy between entrepreneurial and routinized innovation regimes.

Variation in the theoretical perspectives has been accompanied with varied and often conflicting findings in the empirical literature. For example, Audretsch (1991) estimates a logit model and reports that small-firm innovation rate increases survival rate among US firms. However, using the same dataset and a Cox hazard model, Audretsch and Mahmood (1995) report that small firm innovation rate has no effect. Cefis and Marsili (2005) estimate a parametric duration model with data on Dutch manufacturing firms and report that innovative firms have higher survival probabilities. Nevertheless, Jensen et al (2008) and Buddelmeyer et al. (2010) report that the effect on survival depends on the riskiness of the innovation measure in empirical work. These studies find that trademark applications (as a measure of low-risk investment in innovation) increases survival for both new and incumbent firms; but patent applications (high-risk investments) have no effect on survival. Yet, in the UK context, Helmers and Rogers (2010) report just the opposite: firms with at least one patent or trademark application have higher survival probabilities; and firms with larger numbers of higher-quality (hence higher-risk) patents tends to have even higher survival probabilities.

Such heterogeneity in the evidence base may be due to differences in sampling, estimation methods or innovation measures used. Nonetheless, such differences do not seem to have generated varied and conflicting results concerning the effects of other firm-specific factors such as age and size. Nor do they seem to generate varied/conflicting findings on the role of industry-specific factors such as industry growth or macroeconomic factors such as volatility or currency appreciation.[1]

Therefore, we are of the view that differing and conflicting findings on the innovation-survival relationship reflect the inadequacy of the linear specifications used in empirical models. Stated differently, the existing models yield an 'average' effect-size estimate that can be either positive or negative - depending on the level of competition and the riskiness of the innovation investments that characterize the data at hand, but overlooked by the linear model used. Therefore, we propose a quadratic model that would capture various sources of non-linearities in the innovation-survival relationship and the mediating role played market structure. The quadratic model is justified because of theoretical and empirical findings indicating that:

- The relationship between product-market competition and innovation depends on the initial level of competition assumed (see the comprehensive review by Gilbert, 2006);
- The relationship between product-market competition and innovation is non-linear (Aghion et al, 2005; 2009; Tingall and Poldahl, 2006; Berubé et al, 2012; Polder and Veldhuizen, 2012; Hashem and Ugur, 2013);
- Competition and productivity growth also displays non-linear relationship: starting from an initially low level of competition, higher competition stimulates growth; but starting from a high initial level of competition, higher competition has a less positive or even a negative effect on productivity growth (Aghion et al., 2013);
- The relationship between innovation and firm survival is highly contingent on return uncertainty and limited appropriability of the innovative investments (Ericson and Pakes, 1995; Jensen et al, 2008; Buddelmeyer et al, 2010).

[1] As indicated above, both theoretical and empirical work report convergent findings on the effects of firm age and size. Also, industry growth is usually reported to have a positive effect on survival. Finally, the empirical work tends to be in agreement that exchange rate appreciation, price volatility or output gap have a negative effect on firm survival.

The remainder of this paper is organised as follows. In section 2, we demonstrate why it is necessary to adopt a quadratic specification and why it is necessary to control for market concentration on its own and in interaction with R&D intensity. In section 3, we discuss our data and estimation methodology. Section 4 reports the results from a lognormal survival model chosen on the basis of tests for proportional hazards and Akaike and Bayesian information criteria (AIC and BIC). Results for different R&D types and sources of funding confirm the presence of an inverted-U relationship between R&D intensity and survival probabilities. They also confirm that the effect of R&D intensity on survival is mediated by market concentration- with R&D intensity having stronger positive effects on survival as the level of market concentration increases. In the conclusions section, we summarise the main findings and discuss their relevance for policy, practice and future research.

2. Modelling the relationship between R&D and survival

Since the pioneering study of Dunne et al (1988) on patterns of firm entry and exit, there has been a sustained research effort towards modeling and estimating post-entry performance. A significant milestone in the empirical research was the special issue of the *International Journal of Industrial Organization* in 1995, in which Geroski (1995) distilled the stylised facts and empirical patterns indicated above.

The empirical work has been informed by four theoretical perspectives. The evolutionary approach of Nelson and Winter (1982) has informed studies that distinguish between an 'entrepreneurial regime' in which new firms have an innovative advantage over established firms and a 'routinized regime' where incumbents have an advantage over new comers. In the former, new firms are innovative and innovation increases survival rates. In the latter, innovation is less likely and innovative entrants have lower probabilities of survival (Audretsch, 1991; Audretsch and Mahmood, 1995).

The stochastic models draw on stochastic evolution models by Hart and Prais (1956), Simon and Bonini (1958) and Adelman (1958). In the early models, firm dynamics (entry and exit) are determined by idiosyncratic shocks rather than firm-specific factors. Jovanovic (1982; 1994) was the first to incorporate a firm-specific element into the stochastic models. Here, the firm faces productivity shocks that are drawn from a distribution with known variance but unknown mean – which is specific to the firm. The firm decides to enter or exit when it discovers the mean of the productivity shock it is faced with. Although exit and entry generates an equilibrium selection, but the probability of entry and exit (i.e., the probability of survival) is distributed stochastically across firms and independent of observable firm or industry characteristics, including innovation.

Ericson and Pakes (1995) is the first study that allows firms to invest in innovation and discover actively whether it would be more profitable to stay in or exit the industry. In other words, firms are active learners and their entry/exit decisions depend on the stochastic outcome of their investment, the success of other firms in the industry, and the competitive pressure from outside the industry. The model predicts that higher levels of investment in innovation are associated with higher levels of uncertainty and thus lower survival rates. The implication is that it is necessary to allow for heterogeneity in the innovation-survival relationship if the levels of uncertainty associated with a given level of innovation differs between industries or technology classes – an issue not addressed by Ericson and Pakes (1995) but we aim to address here.

Around the same time, Dixit (1995) draws attention to 'deterministic' factors, particularly to the role of sunk costs and the ways in which the latter can induce hysteresis in firms' entry and exit decisions. In Dixit (1995), the firm chooses between entry or exit on the basis two trigger prices. If we consider the entry and exit costs as sunk costs, the firm is faced with two trigger prices. The *trigger price for entry is higher* than the sum of the variable costs and the interests paid on entry cost; but *the trigger price for exit is less* than the difference between variable cost and the interest on the exit cost. The gap between optimum entry and exit triggers is a source of "hysteresis", defined as "the failure of an effect to reverse itself as its underlying cause is reversed."

Due to hysteresis, firms are slow in entering the market even though entry is profitable; and they are also slow in exiting even though exit is optimal. If hysteresis is at work, estimating a linear relationship between innovation and survival boils down to estimating a relationship between innovation and delayed entry and exit. To correct for this bias, we need to account for whether the relationship between innovation and survival differs at different levels of market concentration, which enable firms to derive different levels of rents that can induce faster or slower entry or exit decisions.

What emerges from the work above is that the effect of innovation on firm survival may not be monotonic. The effect is likely to depend on the riskiness of the innovation, the nature of the productivity shock it entails, the innovation/technology regime in place, and the extent to which larger firms or firms in concentrated markets are able to resist short-run deteriorations in their market values. Given these mediating factors, it is necessary to model and test a non-monotonic effect, which depends on the technological distance between the leaders and the followers (the state of the industry) and on the transition of the industry from one state to the other.

In Schumpeterian models of innovation, the non-linear relationship between competition and innovation (which is usually measured as R&D intensity) is driven two factors. The first factor is the initial level of competition, which can be low or high. The second is the speed with which an industry moves from a *levelled* to an *unlevelled* state in terms of technology. A *levelled* industry consists of firms that are neck-and-neck in terms of technology; whereas an *unlevelled* industry is characterised by a large gap between technology leaders and laggards.

In *levelled* industries, increased competition makes life more difficult for neck-and-neck firms and encourages them to innovate in order to escape competition. As a result of this *escape-competition effect*, an increase in competition within levelled industries will be associated with increased R&D intensity in the industry. The escape-competition effect and the increase in R&D intensity will be observed irrespective of the initial level of competition.

In contrast, increased competition in *unlevelled* industries has an ambiguous effect on firms' innovation effort. On the one hand, increased competition may discourage laggard firms from innovation if the initial level of completion is high – i.e., if the prospect for extracting innovation rents is weak. This is the *Schumpeterian effect*, which leads to constant or lower R&D intensity at the industry level following an increase in competition. On the other hand, if competition increases from an initially low level to begin with, increased competition may induce laggard firms to innovate. In this case, increased competition is associated with increased R&D intensity within the industry. Overall, in *unlevelled* industries, the initial level of competition (market concentration) matters and R&D intensity may or may not increase in response to increased competition. The outcome will depend on whether the *escape competition effect* or *Schumpeterian effect* dominates.

Although the fractions of the *levelled* and *unlevelled* industries are given in the steady state, the fractions observed at any given time are endogenous to innovation intensities in both industries. These real-time fractions depends on the speed with which an industry moves from the *levelled* to the *unlevelled* state or vice versa. Aghion et al (2001; 2013) demonstrate that transition from one state to the other also depends on how firms adjust their R&D intensities in reaction to an increase in competition.

If the industry is *unlevelled* and the initial level of competition is high to begin with, an increase in competition will cause the industry to spend more time in the *unlevelled* state. This is because increased competition have an ambiguous effect on R&D intensity as both Schumpeterian and escape-competition effects are at work. However, if the initial level of competition is high and the industry is *levelled*, the industry will move quickly from the levelled to *unlevelled* state. This is because an increase in competition from an initially high level will provide strong incentive for firms that are just behind the technology leader to innovate and overtake the leader. However, as the laggards innovate and overtake leader, the industry quickly moves away from the levelled to unlevelled state.

Hence, when the initial level of competition is high to begin with, an increase in competition will cause both the levelled and unlevelled industries *to spend more time in the unlevelled state*. Because both Schumpeterian and escape competition effects are at work in the *unlevelled state*, the level of R&D intensity is lower than what we would have observed in a *levelled* industry.

In contrast, when the initial level of competition is low to begin with, there is little or no incentive for firms in the *levelled* industry to innovate in response to a given increase in competition. Thus, the industry will spend most of the time in the *levelled* state. On the other hand, when the initial level of competition is low and the industry is *unlevelled* the escape-competition effect will dominate and laggard firms will catch up with technology leaders. Consequently, when the initial level of competition is low to begin with, an increase in competition will cause both the levelled and unlevelled industries to *spend more time in the levelled state*. Because the escape-competition effect is dominant in the *levelled state*, the level of R&D intensity is higher than what we would have observed in an *unlevelled* industry.

The analysis above suggests that the *initial level* of competition mediates the effect of R&D investments on firm survival. When the initial level of competition is high, the industry will spend longer spells in the unlevelled state where the Schumpeterian effect discourages investment in R&D. As a result, radical changes in R&D intensity are less likely and the relationship between innovation and survival is weaker. However, when the initial level of competition is low, the industry will spend longer spells in the levelled state where the escape competition effect is dominant. In this case, radical changes in R&D intensity are more likely and the relationship between innovation and survival is stronger. In the light of these dynamics, we propose the following hypothesis:

Hypothesis 1: *The level of market concentration itself may not have a direct effect on firm survival, but firms are more likely to respond to increased competition by increasing their R&D effort when the initial level of competition is low (i.e., when the initial level of market concentration is high). Hence, an increase in R&D intensity will have a positive effect on survival when the firm is already in relatively more concentrated industries.*

In both Ericson and Pakes (1995) and in Aghion et al. (2001; 2013), increased innovation leads to higher turnover rates, defined as the sum of entry and exit rates. Higher levels of turnover reflect higher levels of creative destruction in the Schumpeterian models, which yield an inverted-U relationship between turnover rates and productivity levels (Aghion et al., 2013). Combining the two, the relationship between innovation effort and productivity must also follow an inverted-U pattern: a given increase in R&D intensity boosts productivity when the initial level of R&D intensity is low; but the effect on productivity diminishes and becomes negative when R&D intensity increases from a high level to begin with.

This by-product of the Schumpeterian models is consistent with both case-study and empirical evidence on the relationship between the level of R&D intensity and productivity of the R&D projects. These studies indicate that the productivity of R&D projects tends to diminish with size because large-size R&D projects are usually observed in firms closer to the technology frontier, where the probability of success (i.e., the probability of securing a breakthrough innovation) is low. Pamamolli et al. (2011) and DiMasi and Grabowski (2012) provide extensive evidence on this pattern in the pharmaceutical industry, where R&D productivity is low or negative because of an increasing concentration of large R&D projects in areas where the risk of failure is high. On the other hand, Kortum (1993) demonstrate that the stock of patents has fallen as the R&D intensity has increased in 20 US manufacturing industries – and the fall in the patents/R&D ratio could not be explained by increased demand. Finally, Czarnitzki and Toole (2013) report that market uncertainty is higher for larger projects, and investment in such projects are usually undertaken by firms in highly concentrated industries – where survival is a function of the interaction between market power and R&D intensity rather than productivity of the R&D investment per se. In the light of this analysis, we derive two further hypotheses on the innovation-survival relationship, assuming a given level of market concentration.

Hypothesis 2: *When the initial level of R&D intensity is low, an increase in R&D intensity leads to longer survival times because the risk associated with increased R&D intensity is relatively low and the increased R&D intensity is likely to move the industry from an unlevelled to a levelled state where innovation has an escape competition effect.*

Hypothesis 3: *When the initial level of R&D intensity is high, an increase in R&D intensity will have a relatively smaller positive effect or a negative effect on survival because an increase in R&D intensity from an initially high level is associated with lower R&D productivity and/or higher failure probabilities.*

The analysis above suggests that the direct effect of market concentration on survival is ambiguous. The hypothesized ambiguity is in line with earlier findings reported in the empirical literature. For example, Mata and Portugal (1994) and Wagner (1994) report insignificant effects; McCloughan and Stone (1998) report an inverted-U relationship between concentration and survival, but the coefficient on the linear term is insignificant; and Baldwin and Rafiquzzaman (1995) report a positive and significant linear relationship. However, we hypothesize that the interaction between market concentration and R&D intensity of the firm does matter: firms with higher levels of R&D intensity are more likely to survive if they are in a concentrated market. This is because innovative firms in concentrated markets are more likely to secure monopoly profits as a result of innovation.

The analysis above also suggests that the relationship between R&D intensity (which depends on the initial level of market concentration and whether the firm is in a *levelled* or *unlevelled* industry) and survival is non-monotonic. The relationship is likely to follow an *inverted-U pattern* because: the effect of R&D intensity on survival is mediated though: (i) an *inverted-U* relationship between creative destruction and productivity; and (ii) higher risks of failure (or lower returns on R&D projects) as R&D intensity increases.

Given these conclusions, we can specify the survival model in terms of accelerated failure time (duration) or hazard rates.

$$logt_j = \mathbf{X}_j\beta + z_j \qquad (1)$$

$$h(t_j) = h_0(t)exp(\mathbf{X}_j\beta) \qquad (2)$$

Where, $logt_j$ in (1) is survival time, $h(t_j)$ in (2) is hazard rate, $\mathbf{X}_j$ is a vector of covariates that affect survival time, β is a vector of coefficients to be estimated, and z_j is the error term. In the methodology section below, we discuss which specification we choose and why. For the moment, we limit ourselves to specifying the covariates in $\mathbf{X}_j$.

In the light of the discussion above, the covariates should include R&D intensity, square of R&D intensity, a measure of market concentration, its square, and an interaction term between market concentration and R&D intensity. Also, the stylised facts and empirical patterns indicated above suggest that a number of other firm, industry and macroeconomic factors should also be included in $\mathbf{X}_j$. Hence the vector $\mathbf{X}_j$ can be defined as follows:

$\mathbf{X}_j$=(*RD_int, RD_int_sq, HI, RD_int*HI, Other_firm_covs, Other_ind_covs, Macro_covs*).

The full list of the covariates and expected signs are indicated in Table 1 below.

Of the covariates of main interest (1 – 4), the R&D intensity and its square enables us to test for an *inverted-U* relationship between R&D intensity and survival in accordance with hypotheses (2) and (3). An increase in R&D intensity has a positive effect on survival when the initial level of R&D intensity is low, but the effect is dampened and becomes negative at higher levels of R&D intensity. So far, only Sharapov et al (2011) have tested for quadratic relationship between R&D intensity and survival. Estimating a proportional hazard model, they report an *inverted-U* relationship between R&D intensity and hazard rates. This finding, however, is the opposite of what we expect – given the theoretical models of competition, innovation and firm survival in Aghion et al (2001; 2013) and Ericson and Pakes (1995). As indicated in hypotheses (2) and (3), the *inverted-U* relationship should be observed between R&D intensity and *survival* – not between R&D intensity and hazard rates: the latter should have *U-shape*.

Covariates (3) and (4) are necessary to test for Hypthesis 1. We expect the direct of effect of market concentration on survival to be ambiguous. This is in accordance with Hypothesis (1) – and tallies with reported findings in the empirical literature. As indicated above, McCloughan and Stone (1998) and Baldwin and Rafiquzzaman (1995) find a significant relationship between market concentration and firm survival. However, Mata and Portugal (1994) and Wagner (1994) report insignificant effects. This is not surprising because the level of market concentration can have two opposite effects on firm survival. On the one hand, it may allow firms to enjoy higher price-cost-margins that should, *ceteris paribus*, increase the probability of survival. On the other hand, highly concentrated markets may be subject to aggressive behaviour by rivals which may reduce chances of survival.

The expected signs for other covariates (categorised into firm-specific, industry-specific and macroeconomic environment factors) are informed by the stylised facts and empirical patterns reported in the literature. The relevant literature for each expected effect is listed in the last column of Table 1.

Table 1: Factors affecting firm survival

Covariate	Description and (expected effect)	Related literature
Covariates of main interest		
1. R&D intensity	R&D intensity - R&D expenditures over sales for different R&D types and sources of funding (+)	Aghion et al (2001; 2013); Ericson and Pakes (1995); Sharapov et al (2011)
2. R&D int. sq.	Square of R&D intensity (-)	Aghion et al (2001; 2013); Ericson and Pakes (1995); Sharapov et al (2011)

3. Herfh. Index (HI)	Herfindahl-Hirschman index calculated at 3-digit industry level (+ / -)	McCloughan and Stone (1998); Baldwin and Rafiquzzaman (1995); Wagner (1994)
4. (R&D. int.)(HI)*	Product of R&D intensity and Herfindahl-Hirschman index (+)	Aghion et al (2001; 2013); Ericson and Pakes (1995)
Other firm-level covariates		
5. Age	Firm age in years (+)	Hopenhayn (1992); Ericson and Pakes (1995); (Geroski, 1995); Cefis and Marsili (2005); Doms et al (1995); Disney et al (2000)
6. Size	Number of employees (+)	Hopenhayn (1992); Ericson and Pakes (1995); (Geroski, 1995); Cefis and Marsili (2005); Doms et al (1995); Disney et al (2000)
7. Size_sq	Square of number of employees (-)	Hopenhayn (1992); Ericson and Pakes (1995); (Geroski, 1995); Cefis and Marsili (2005); Doms et al (1995); Disney et al (2000)
8. Live_lu	Indicates multi-plant firm if live local unit is 1 or greater (+ / -)	Audretsch and Mahmood (1995)
9. Productivity	Deflated turnover per employees (+)	(Audretsch, 1991) Hopenhayn (1992); Ericson and Pakes (1995)
10. Growth	Growth of deflated turnover (+)	(Audretsch, 1991) Hopenhayn (1992); Ericson and Pakes (1995); Cefis and Marsili (2005); Mata et al (1995); Agarwal (1997).
11. Civil R&D	Dummy variable indicating that firm is engaged only in civil R&D - firms engaged in defence only or in defence and civil R&D are excluded category (+ / -)	Not tested before.
12. UK_owned	Ownership dummy indicating that firm is UK-owned – non-UK firms are excluded category (+ / -)	Sharapov et al (2011)
Industry covariates		
13. Pavitt technology class	Four dummy variables for 4 Pavitt classes - excluded category is Pavitt class dominated by technology suppliers (+ / -)	(Pavitt, 1984); (Agarwal and Audretsch, 2001); Cefis and Marsili (2005)
Macroeconomic factors		
14. Crisis year	A dummy variable equal 1 for the Asian crisis year of 1998; *dot.com* bubble crisis of 2001; and start of the recent financial crisis in 2008 (-)	Not tested before; but Bhattacharjee et al (2009) report higher hazard rates in periods of volatility.
15. Effective exchange rate	Average effective exchange rate defined against a basket currencies - an increases in *A_reer* indicates domestic currency appreciation (-)	Bhattacharjee et al (2009); Goudie and Meeks (1991)
16. FTSE350	Stock market index for FTSE 350 (+)	(Jensent et al, 2008)

3. Data and methodology

Our dataset is constructed by merging two ONS databases: the Business Structure Database (BSD) and the Business Expenditure on Research and Development (BERD). The BSD contains demographic data on firm births, deaths, number of local units, ownership, location, etc.; and a limited range of firm-level variables such as employment and turnover. Each firm (enterprise) is identified with unique identifier (*entref*); whereas each local unit (plant) with the enterprise is identified with unique local-unit identifier (*luref*). We merged the BSD with BERD, using the unique firm identifier (*entref*). We constructed consistent standard industry classification (SIC) codes based on the latest codes adopted in 2007, obtaining SIC codes at 1-digit, 2-digt and 3-digit industry levels.

BERD is a rich database on R&D expenditures and their sources of funding. The sample includes around 400 largest investors in R&D plus a stratified sample based on size (employment). Hence, while BSD contains information on the firm every year until it is dead, firms in BERD do not necessarily appear in the sample every year. Nevertheless, the number of firms in BERD has increased over years and it was possible to have a match for 45,082 firms (entrefs) in total. However, the final sample for estimation consists of 39,705 firms (entrefs) as we excluded firms in the top 1% of the R&D intensity distribution. The distribution of R&D intensity is known to be highly skewed with a long right tail (Aghion, 2013). This is found to be the case in BERD too, with the added property that the R&D intensity of some firms in the top 1% of distribution constitutes very large multiples of their turnover or employment for repeated years. These are usually one-person innovators or venture-capital innovators.[2] Summary statistics for the estimation sample are presented in Tables A1 and A2 in the *Appendix*.

First, we conduct *nonparametric* analysis of the data, without any assumptions about the functional form of the survivor function. For this, we use the Kaplan-Meier estimator of the survivor function $S(t)$ and the Nelson-Aalen estimator for the cumulative hazard $H(t)$.

$$S(t) = \Pi_{s<t} \frac{N_s - D_s}{N_s}; \quad and \quad H(t) = -\ln[S(t)] \qquad (3)$$

Here, where t is analysis time; $H(t)$ is the cumulative hazard function or a total number of expected firm exits until time t; N_s is the number of firms at risk at time s; and D_s is the number of failures ('natural deaths') at time s. In large samples such as ours (39,705 firms and 183,105 observations), both estimators deliver similar results. Therefore, we report nonparametric results for the survival function only.

Then we proceed to provide estimates adjusted for the effects of observed firm, industry and macroeconomic variables which are known to affect cumulative hazard or survival, including R&D intensity. Two types of models for adjusting survivor functions for the effects of covariates

[2] Exclusion of the firms in the top 1% of the R&D intensity distribution did not affect the sign and significance of the parameters of interest (R&D intensity, its square and the interaction between R&D intensity and the Herfindahl index. The effect was limited to coefficient size. Estimation results are not reported here, but are available on request.

are the proportional hazards (PH) and the accelerated failure-time (AFT) models. In the PH model, the covariates have a multiplicative effect on the hazard function, as indicated in (4) below.

$$h(t_j) = h_0(t)g(\mathbf{x}_j) = h_0(t)\exp(\mathbf{x}_j\beta) \qquad (4)$$

Here, j is firm, $\mathbf{x}$ is a vector of covariates that capture firm-, industry- and macro-level factors assumed to affect cumulative hazard and β is a set of parameters to be estimated. The baseline hazard $h_0(t)$ can be left either unspecified yielding a Cox PH model; or it can be specified as a parametric function, yielding a range of parametric PH models including exponential, Weibull, and Gompertz.

On the other hand, one can estimate an accelerated failure-time (AFT) model of survival. In the AFT model, the natural logarithm of the survival time, *log(t)*, is expressed as a linear function of the covariates, yielding the linear model in (5).

$$logt_j = \mathbf{x}_j\beta + z_j \qquad (5)$$

Here, z_j is the error term and all other terms are as described above. The error term has a density function *f( )*, the distributional form of which can be: (i) normal density (yielding a log-normal regression); (ii) logistic density (yielding a log-logistic regression); or extreme value density (yielding a Weibull regression).

Our estimation strategy follows an iterative processes. First, we estimate a PH Cox model that assumes a non-parametric baseline hazard. The PH Cox model assumes that covariates shift the baseline hazard function for the j[th] firm in form of $h_j(t) = h_0(t)exp(\beta'x)$. Here $h_0(t)$ is the baseline hazard function; x is the matrix of covariates; and β is a vector of regression coefficients. Taking logarithm: $log\ [h_j(t)/h_0(t)] = \beta 1X1i + \beta 2X2i + \beta 3X3i + ...+ \beta kXki.$ Note that ratio $h_j(t)/h_0(t)$ is fixed, but a particular form of $h_0(t)$ is not known.

Then we estimated a range of *parametric* PH and AFT models (*exponential*, *Weibull*, *Gompertz*, and *log-normal*) to ascertain the preferred model on the basis of *AIC* and *BIC* information. Right censoring when firm exit has not occurred during the observation period or when firm disappears from the ONS register for unknown reasons can be dealt with in the parametric models. In these models, the origin of time at risk is important and we set it from the start of our sample observation in 1997. The likelihood function of estimated parametric models is as indicated in (6) below.

$$L_i(\beta,\gamma) = [S(t_i|X_i\beta_x,\gamma)]^{1-di}[f(t_i|\ X_i\ \beta x,\gamma)]^{di}/\ S(t_{0i}|X_i\ \beta x,\gamma) \qquad (6)$$

Here, f is the density function of the assumed distribution, S is survival function, t_i is duration time between firm entry and exit for the i[th] observation, and t_0 is the beginning of the observation period. At time t_i the firm either exits (d_i = 1) or is right-censored (d_i = 0). $S(t_{01}|Xi\ \beta x,\gamma)$ is the probability for a firm to survive up to time t_{01}, parameters $\beta x, \gamma$ are estimated with maximum likelihood method. We fit four non-nested models: exponential, Weibull, Gompertz, and log-normal and choose the preferred (optimal) model using the minimum of the Akaike and Schwartz (Bayesian) information criteria (*AIC* and *BIC*).

We define firm exit (failure) as either the death year indicated in the Business Structure Database (BSD) of the Office of National Statistics (ONS) or as the first year when the firm employment and turnover are zero for 3 consecutive years. This is done to correct for administrative delays in recording the correct death year. BSD is an annual snapshot of the Interdepartmental Business Register (IDBR), which contains all firms registered for value-added tax (VAT) or income tax through the pay-as-you-earn (PAYE) system.

Firms in BSD have two identifiers: (i) an enterprise identifier for each firm, which may be a single-plant or multi-plant firm; and (ii) a local unit identifier for each local unit (plant) within the firm, including the firm itself if the latter is a single-plant firm. We differentiate between firm exit due to corporate market transactions (mergers, acquisitions or outright sale) and firm exit due to liquidation or bankruptcy ('natural death'). This is done by establishing whether the local unit reference for local units within a multi-plant firm or for a single-plant firm itself survives the enterprise reference. If the local-unit reference survives the enterprise reference in IDBR, firm exit is coded as exit due to corporate market control. Such exist are not included in the estimation sample, which consists of exits due to 'natural death' only. Firm age is defined as the difference between a current period and a firm's year of birth. The survival analysis is conducted on the basis of analysis time – which is equal to the difference between the current year and the firm's entry into the dataset.

Proportional hazard models assume a continuous hazard function – i.e., there are no tied survival times. However, tied events do occur in survival data because of the way in which time is recorded. If tied events occur, the likelihood reflects the marginal probability that the tied-failure events occurred before the non-failure events in the risk pool. Finally, the risk pool for each tied failure event is the sum of non-failure subjects (firms).

The range of covariates in the PH and AFT models of (4) and (5) is informed by the literature indicated in Table 1 above and by the three hypotheses we wish to test (see above). Our hypotheses require R&D intensity, its square, Herfindah-Hirschman index (HI) as a measure of concentration at 3-digit industry level, its square, and an interaction term consisting of R&D intensity multiplied with HI. To reduce heterogeneity, we use the logarithm of the covariates unless the latter are defined as dummy variables or ratios between 0 and 1.

R&D intensity is calculated as R&D/turnover for all types of R&D expenditures and funding sources (see summary statistics tables - Table A1 and A2 - in the *Appendix*). . The HI is calculated at 3-digit industry level, using consistent the standard industrial classification code (SIC) adopted in 2007. Firm growth is calculated as the log difference of turnover in two successive years, using the ONS 2-digit output deflator to obtain deflated turnover. As indicated above, firm age is calculated as the difference between current year (t) and the birth year of the firm as recorded in IDBR. The birth year for firms that entered the IDBR in the first year of its existence (i.e., in 1973) were all given 1973 as the birth year, despite the fact that some firms in this first cohort were born before 1973 (see Riegler, 2012). Therefore, we will estimate the preferred model with firms born in 1974 or after.

We also control for a range of firm-, industry- and macro-level variables. Of these, size is measured by headcount employment; live local unit is the number local units other than the head-quarters of the firm (hence single-plant firms will have 0 local unit); deflated turnover per employee as a measure of productivity; growth of deflated turnover as a measure of firm growth; a civil dummy that indicates that the firm is not engaged in defence-related R&D; a UK ownership dummy that indicates that the firm is not foreign-owned; four dummies for 4 Pavitt technology classes (Pavitt, 1984), with unclassified firms treated as excluded category; yearly average effective real exchange rate, defined as the price of domestic currency vis-à-vis a basket of currencies for UK's major trading partners (Bank of England data); yearly FTSE-350 index; and a crisis dummy that takes the value of 1 for crisis years of 1998 (east Asian crisis), 2001 (the dot.com bubble crisis) and 2008 (the fir year full-year of the recent financial crisis). The FTSE-350 index and the average effective exchange rate are used as indicators of time shocks that may affect all firms. Whilst the FTSE-350 index reflects the profitability expectations of the market participants for the year, the average real effective exchange rate reflects the competitiveness of UK firms.

The preferred model chosen on the basis of AIC and BIC is first estimated in a step-wise fashion to verify if the main coefficients of interest (i.e., R&D intensity, its square, the Herfindal index, its square and the interaction between R&D intensity and the Herfindahl index) remain robust to model specification. Then, we estimate the full model with different samples. First, we estimate the full-model with firms born in 1974 and thereafter (post-1973 sample) to isolate the likely bias that may arise from incorrectly recorded firm age for firms born in 1973 or before. In the second step, we re-estimate the model with the same sample, using lagged values of the firm-level covariates in order to minimise the risk simultaneity. In the third step, we take account of left truncation (i.e., lack of information on firms that entered the IDBR before our first year of data in 1997) by estimating the preferred model with firms that entered the IDBR in 2000 or thereafter.

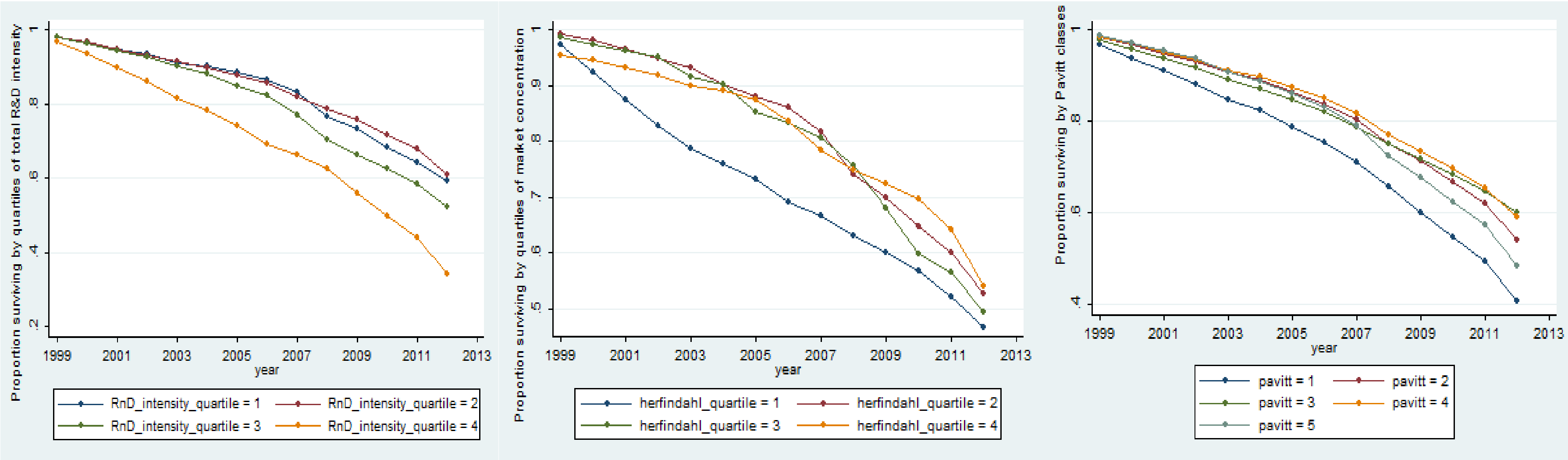
Finally, we estimated the model with different R&D types, including: (i) total R&D intensity; (ii) extramural R&D intensity that measures the intensity of the R&D commissioned from outside the firm; (iii) intensity of R&D expenditures on capital investment; (iv) intensity of current R&D expenditures; (v) intensity of privately-funded R&D (R&D funded from firm funds and other private funds including parent company); and (vi) publicly-funded R&D intensity (R&D funded by direct support for the UK government and/or the European Commission).

4. Results

In what follows, we first present non-parametric estimations of survival rates – by R&D intensity quartiles, market concentration quartiles, and Pavitt technology classes.

Figure 1: Non-parametric survival estimations

Survival rates by R&D intensity quartile | Survival rates by Herfindahl index quartile | Survival rates by Pavitt technology class



The estimates above are based on Kaplan-Meier survivor estimators of the survival functions. They indicate that: (i) firms in the 3rd and 4th quartiles of the R&D intensity (i.e., above-median R&D intensity) tend to have lower survival rates; (ii) firms in the lowest quartile of the market concentration has lower survival rates compared to the remaining 3 quartiles; (iii) the survival rates in other quartiles do not display a clear pattern; (iv) Pavitt class 1, which consists of science-based technology industries has the lowest survival rate, followed by Pavitt class 3 (scale-intensive industries). The difference between survival rates summarised above has been confirmed by *Log-rank*, *Wilcoxon*, *Tarone-Ware* and *Peto-Peto* tests. The null hypothesis about the equality survival rates by R&D intensity quartile, by market concentration quartile and by Pavitt class has been rejected.[3]

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[3] Also, the nonparametric tests reject the equality of survival functions across quartiles of employment as proxy for firm size and for the crisis and non-crisis years. Test results are not reported here to save space, but they are available on request.

Hence, the non-parametric results indicate that *higher* levels of R&D intensity are likely to be associated with *lower* survival rates. In other words, the Schumpeterian creative destruction dynamics are likely to be observed at the top end of the R&D intensity distribution. The graphs also indicate that firms tend to have lower survival rates when the initial level of market concentration is low. However, the closeness and crossing of the survival function estimates for quartile 2-4 of the Herfindahl index also indicate that market concentration on its own may not be a significant determinant of survival. Finally, the graphs indicate firms have lower survival durations when they are located within a science-based industry (Pavitt 1) compared to other classes. However, firms in the Pavitt class 2 (specialised suppliers of technology) and Pavitt class 5 (unclassified firms) tend to longer survival durations.

However, it must be indicated that the results from non-parametric estimations may not be reliable as they are not conditioned on other factors (firm, industry and macroeconomic variables) that also affect survival. The estimations results below will address this issue and provide a fuller picture about the effect of all covariates on survival. The proportional hazard (PH) and accelerated failure time (AFT) models to be estimated, respectively, can be specified as follows.

$$h(t_j) = h_0(t)g(\mathbf{x}_j) = h_0(t)\exp(\beta_0)\exp(\beta_1 RD\_int_j + \beta_2 RD\_int\_sq_j + \beta_3 HI_j + \beta_4 HI * RD\_int_j + \beta_5 Age_j + \beta_6 Empl_j + \beta_7 Empl\_sq_j + \beta_8 Live\_lu_j + \beta_9 Prod_j + \beta_{10} Growth_j + \beta_{11} Civil\_RD_j + \beta_{12} UK\_firm_j + \beta_{13} Pavitt1_j + \beta_{14} Pavitt2_j + \beta_{15} Pavitt3_j + \beta_{16} Pavitt5_j + \beta_{17} Areer_j + \beta_{18} Crisis_j + \beta_{19} FTSE\_350_j) \quad (4a)$$

$$logt_j = \beta_0 + \beta_1 RD\_int_j + \beta_2 RD\_int\_sq_j + \beta_3 HI_j + \beta_4 HI * RD\_int_j + \beta_5 Age_j + \beta_6 Empl_j + \beta_7 Empl\_sq_j + \beta_8 Live\_lu_j + \beta_9 Prod_j + \beta_{10} Growth_j + \beta_{11} Civil\_RD_j + \beta_{12} UK\_firm_j + \beta_{13} Pavitt1_j + \beta_{14} Pavitt2_j + \beta_{15} Pavitt3_j + \beta_{16} Pavitt5_j + \beta_{17} Areer_j + \beta_{18} Crisis_j + \beta_{19} FTSE\_350_j + z_j \quad (5a)$$

Abbreviations refer to the following variables:

RD_int is R&d expenditures as a ratio of turnover. The models are estimated with six different R&D intensities: total R&D intensity; extramural R&D intensity; intensity of R&D expenditures on capital (labs, instruments, machinery, etc.); intensity of current R&D expenditures; intensity of privately-funded R&D expenditures; and intensity of publicly-funded R&D intensity (UK and EU funded R&D).

RD_int_sq is the squared value of each R&D intensity defined above.

HI is the Herfindahl-Hirschman index, calculated as a measure of market concentration at 3-digut industry level.

*HI*RD_int* is the interaction term for R&D and concentration, with *RD_int* corresponding to each of the R&D intensities defined above.

Age is firm age in years.

Empl is headcount employment as a measure of size from IDBR, including part-time and full-time workers. IDBR employment is based on firms' PAYE returns;

Empl_sq is the squared value of employment as defined above.

Live_lu is the number of live local units, apart from the firm's headquarters.

Prod is a measure of productivity, calculated as deflated turnover per employee.

Growth is the annual growth rate, calculated as log difference of deflated turnover.

Civil_RD is a dummy indicating that the firm is engaged in civil R&D only. The excluded category is firms engaged partly or fully in defence-related R&D.

UK_firm is a dummy indicating that the firm is owned by UK natioanls. The excluded category is all firms owned by non-UK nationals.

Pavitt1 is Pavitt technology class that consists of firms within science-based industries such as chemicals, information technology, office machinery, precision instruments, and medical and optical instruments industries (35% of the firm/year observations). The excluded category is Pavitt class 4, which consists firms within technology-supplier-dominated industries such as textiles & clothing, food & drink, fabricated metals, etc. (27% of the firm/year observations).

Pavitt2 is Pavitt technology class that consists of firms within industries that are specialized suppliers of technology or capital goods to other industries such as mechanical engineering industries, manufacturers of electrical machinery, equipment hire&lease industries, and business services suppliers (22% of the firm/year observations). The excluded category is Pavitt class 4.

Pavitt3 is Pavitt technology class that consists of firms within scale-intensive industries such as pulp&paper, transport vehicles, mineral oil refining industries, financial intermediaries, etc. (9% of the firm/year observations). The excluded category is Pavitt class 4.

Pavitt5 is Pavitt technology class that consists of firms within unclassified industries (7% of the firm/year observatuions). The excluded category is Pavitt class 4.

Areer is the average effective exchange rate, defined as the price of UK currency against a basket of currencies of the UK's major trading partners. An increase in *Areer* indicates appreciation of the UK currency.

Crisis is a dummy equal to 1 for years 1998 (the east Asian crisis), 2001 (the burts of dot.com bubble), and 2008 (the first full-year of the recent financial crisis.

FTSE_350 is the share price index for the largest 350 UK companies.

The inclusion of R&D intensity and its square will enable us to test hypotheses 2 and 3 derived n section 2; whereas the inclusion of the Herfindahl index and its interaction with R&D intensity will enable us to test hypothesis 1. The expected sigs are as follows: *RD_int* (+); *RD_int_sq* (-); *HI* (ambiguous or insignificant); and *HI*RD_int* (+).The remaining covariates are included in the model on the basis of existing empirical work. The relevant empirical studies and the expected signs of these covariates are indicated in Table 1 above.

Following the non-parametric tests, we estimated model (4a) with a PH Cox specification, which assumes that covariates shift the baseline hazard function for the j^{th} firm in form of $h_j(t) = h_0(t)\exp(\beta' x)$. Here $h_0(t)$ is the baseline hazard function; x is the vector of covariates; and β is a vector of regression coefficients. Note that ratio $h_j(t)/h_0(t)$ is fixed, but the particular form of $h_0(t)$ is not known.

We reject the Cox specification because it fails on specification link test using the likelihood ratio, which is an analogue of RESET test for the OLS estimator. We have also tested for proportional hazard assumptions of the Cox model in the data and had to reject them for the chosen specification. Interaction of the covariates with time came out statistically significant, leading to rejection of the Cox model assumptions. Tests with Schoenfeld (1982) residuals obtained from the Cox model and fitting a smooth function of time for them shows a linear relationship, which also rejects the proportionality assumption. Then, we estimated the model with four parametric PH and AFT specifications, including *exponential*, *Weibull*, *Gompertz*, and *log-normal*. The *AIC* and *BIC* values indicate that the log-normal is the preferred specification as it has the smallest values of AIC and BIC across all types of R&D intensity.[4] Therefore, results reported below are from log-normal specification, which can be estimated in AFT mode.

A positive (negative) and significant coefficient in AFT estimation indicates that the time to failure (i.e., survival time) increases (decreases) as the covariate increases by one unit. An insignificant coefficient indicates no effect of the time to failure. The log-normal estimations in AFT mode take account of right censoring – i.e., the situation when firm exit has not occurred during the observation period or when firm disappears from the ONS register for unknown reasons. The origin of time at risk is set from the start of our sample observation in 1997. In other words, the results presented below are based on analysis time rather than age, which is included in the model as a separate covariate.

Table 2 below presents the results from the lognormal survival model for six types of R&D intensities. The summary statistics for the estimation sample are presented in *Appendix* Tables A1 and A2, which report the summary statistics in level and logs, respectively.[5] The logarithm of some covariates is taken after their values in level are augmented by 1 where necessary to take account of zero (0) values.

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[4] Results are not reported here to save space, but are available on request.

[5] Minimum and maximum values are not reported in Tables A1 and A2 in the Appendix. This is due to non-disclosure requirements of the Secure Data Access unit of UK Data Archive. These statistics will be made available later when UK Data Service verifies that their release will not conflict with the non-disclosure rules.

Table 2: R&D intensity, source of funding and firm survival: firms with birth year > 1973

	Total R&D	Extramural R&D	Capital R&D	Current R&D	Private R&D	Public R&D
Log (R&D intensity + 1)	0.2729***	1.3689***	2.7036***	0.2577***	0.3947***	-1.3934***
	(0.05647)	(0.3713)	(0.4163)	(0.06115)	(0.06455)	(0.1911)
Log (R&D intensity + 1) sq.	-0.1434***	-4.1782***	-9.0264***	-0.1569***	-0.2139***	1.6693***
	(0.02751)	(0.9953)	(1.3796)	(0.03204)	(0.03510)	(0.3355)
Herfindahl index (HI)	-0.04956	0.001795	0.02146	-0.05683	-0.03775	-0.05346
	(0.08064)	(0.07596)	(0.07697)	(0.08045)	(0.08020)	(0.07739)
HI*Log (R&D int.)	0.6100***	1.7538	1.5154	0.7528***	0.6457***	4.0050***
	(0.1714)	(1.6836)	(1.4642)	(0.1856)	(0.1972)	(0.6893)
Log (age + 1)	0.4080***	0.4070***	0.4076***	0.4079***	0.4101***	0.4109***
	(0.01413)	(0.01411)	(0.01411)	(0.01413)	(0.01409)	(0.01425)
Log (employment + 1)	0.2591***	0.2564***	0.2564***	0.2581***	0.2578***	0.2502***
	(0.01759)	(0.01753)	(0.01753)	(0.01758)	(0.01754)	(0.01753)
Log (employment + 1) sq.	-0.02824***	-0.02803***	-0.02801***	-0.02811***	-0.02809***	-0.02725***
	(0.002546)	(0.002542)	(0.002542)	(0.002546)	(0.002542)	(0.002536)
Log (live local unit + 1)	0.02394	0.02408	0.02426	0.02342	0.02449	0.02303
	(0.02008)	(0.02009)	(0.02008)	(0.02009)	(0.02005)	(0.02013)
Log (deflated turnover per employee + 1)	0.1066***	0.09218***	0.1029***	0.1042***	0.1114***	0.07119***
	(0.008413)	(0.007480)	(0.007867)	(0.008410)	(0.008346)	(0.007570)
Growth rate from t-1 to t	0.01987***	0.01859***	0.01853***	0.01965***	0.02111***	0.01692***
	(0.005191)	(0.005107)	(0.005175)	(0.005188)	(0.005210)	(0.005109)
Civil-only R&D firm	0.09196***	0.09410***	0.09106***	0.09236***	0.09032***	0.08677***
	(0.01071)	(0.01069)	(0.01067)	(0.01071)	(0.01068)	(0.01065)
Firm UK owned	0.08343***	0.08036***	0.08210***	0.08310***	0.08494***	0.07297***
	(0.02326)	(0.02328)	(0.02325)	(0.02326)	(0.02323)	(0.02326)
Pavitt class 1	-0.02663	-0.003482	-0.02711	-0.02303	-0.03795	-0.00056
	(0.1035)	(0.1037)	(0.1037)	(0.1034)	(0.1034)	(0.1031)
Pavitt class 2	0.1979***	0.1990***	0.1979***	0.1988***	0.1943***	0.2009***
	(0.06720)	(0.06723)	(0.06727)	(0.06721)	(0.06717)	(0.06706)
Pavitt class 3	0.05278	0.06352	0.05278	0.05477	0.04557	0.06995
	(0.06493)	(0.06503)	(0.06505)	(0.06493)	(0.06489)	(0.06483)
Pavitt class 5	0.09868	0.09450	0.09504	0.1003	0.09803	0.09870
	(0.07729)	(0.07737)	(0.07740)	(0.07728)	(0.07723)	(0.07699)
Real effective exchange rate	-0.06145***	-0.06151***	-0.06139***	-0.06152***	-0.06139***	-0.06174***
	(0.000798)	(0.000796)	(0.000799)	(0.000798)	(0.000797)	(0.000794)
Crisis dummy = 1 in 1998, 2001 and 2008	-0.4741***	-0.4769***	-0.4764***	-0.4740***	-0.4702***	-0.4794***
	(0.00635)	(0.00634)	(0.00634)	(0.00635)	(0.00635)	(0.00637)

Log (FTSE350)	1.0958***	1.0860***	1.0920***	1.0930***	1.1010***	1.0869***
	(0.02948)	(0.02935)	(0.02939)	(0.02949)	(0.02948)	(0.02928)
Constant	-3.5449***	-3.3744***	-3.4707***	-3.4954***	-3.6140***	-3.2011***
	(0.3380)	(0.3361)	(0.3356)	(0.3370)	(0.3387)	(0.3324)
2-digit industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Ln(Sigma)	-0.3110***	-0.3111***	-0.3113***	-0.3108***	-0.3125***	-0.3122***
	(0.006376)	(0.006368)	(0.006392)	(0.006374)	(0.006390)	(0.006443)
Observations	168843	168822	168874	168835	168827	168925
AIC	58216.2	58274.5	58307.8	58221.1	58241.9	58214.9
BIC	59260.0	59318.3	59351.6	59264.9	59285.7	59258.8
Number of subjects	36836	36843	36836	36835	36836	36840
Number of failure times	39990	40034	39945	39981	39972	39937
Log likelihhod	-29004.1	-29033.2	-29049.9	-29006.6	-29016.9	-29003.5

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All firms born in 1974 and after. Observations in the top 1% of the R&D intensity distribution for each R&D category are excluded. Estimation period: 1997-2012.

Results in the top four rows indicate that hypotheses 2 and 3 are supported by the data. The relationship between R&D intensity and survival has an *inverted-U* shape – with notable exception of the publicly-funded R&D intensity. When the initial R&D intensity is low to begin with, an increase in R&D intensity increases the survival time; but the increase is at decreasing rates and the turning points are reach around exp(1) = 2.72, which is the R&D intensity that corresponds to the turning points. In the sample, this level of R&D intensity is observed in the top quartile of the R&D intensity distribution. This finding indicates that the effect of R&D intensity on firm survival mirrors the effect of turnover (creative destruction) on productivity and reflects the higher risks associated with higher levels of R&D investment. It also indicates the existing findings may be due to misspecification bias to the extent that they are derived from a linear specification without testing for significance of a quadratic specification.

Similarly results in rows 5 – 8 indicate that hypothesis 1 is supported by the data. The HI on its own is not statistically significant, but it is significant and positive when interacted with R&D intensity. In other words, the effect of R&D intensity on survival is stronger in more concentrated industries. This is because, in more concentrated industries, a given increase in R&D intensity is more likely to enable the firm to extract innovation rents and increase its chances of survival. The significance of the interaction term is in line with the Schumpeterian proposition that investment in R&D is motivated by the scope for innovation rents. It also indicates failure to control for the interaction between R&D intensity and market structure could be a source of misspecification bias.

When we look at the effects of different R&D types, we observe that extramural R&D (R&D commissioned form outside the firm) and capital-related R&D expenditures (i.e., investment in R&D-related labs, instruments, machinery, etc.) have stronger positive effects on survival time compared to total, current and private R&D. This is to be expected because the level of capital R&D is an indication of technological capacity and cumulative knowledge. Similarly, extramural R&D indicates ability to link with universities and specialised private research institutions. The turning points for capital and extramural R&D intensity are much smaller than those for total, current and privately-funded R&D. This is also to be expected because extramural R&D and capital-related R&D intensity is much smaller (0.009) than total or current R&D intensity (0.158 and 0.137, respectively).

The coefficients on publicly-funded R&D intensity are not in line with hypotheses 2 and 3 above. However, they confirm that the relationship between R&D intensity and survival is non-monotonic, albeit with a U shape. Because publicly-funded R&D is essentially R&D subsidies from the UK government and the European Commission, the negative coefficient on the linear term can be due to funding rules that favour firms already in distress (i.e., firms faced with higher hazard rates at the time of subsidy). Secondly, public subsidies may have a substitution effect, leading to lower R&D effort in terms of privately-funded or total R&D intensity. We do not wish to delve too much into this finding because it is not robust to controlling for left truncation or lagged estimation.

Given that coefficients on the Herfindahl index are not statistically significant, we have checked if the Herfindahl index and its interaction with R&D intensity are jointly significant with likelihood-ratio test and failed to reject joint significance of these variables. Similarly we have failed to reject joint insignificance of the Pavitt class dummies despite the fact that some of the Pavitt class dummies are not individually significant. Finally, Post-estimation of Cox-Snell residuals for all 6 types of R&D show that they approximately satisfy the condition of hazard function equal to one for all time.

Before we discuss the effects of other covariates, we proceed to discuss the findings from various robustness checks. As indicated above, some firms in the dataset are left-truncated in that they existed before 1997 (the initial year in our sample) but they are not observed before 1997. To address this issue, we restricted the sample to firms that enter the dataset in 2000 or after. The estimations results remained the same – as can be seen in Table 3.

Table 3: R&D expenditures, source of funding and firm survival: Entry in 2000 and after

	Total R&D	Extramural R&D	Capital R&D	Current R&D	Private R&D	Public R&D
Log (R&D intensity + 1)	0.3996***	1.5888***	3.1598***	0.3875***	0.5389***	-0.1227
	(0.06831)	(0.4453)	(0.5339)	(0.07408)	(0.07808)	(0.2798)
Log (R&D intensity + 1) sq.	-0.1839***	-4.7307***	-10.007***	-0.1939***	-0.2702***	0.03864
	(0.03472)	(1.3725)	(1.7658)	(0.03993)	(0.04477)	(0.4913)
Herfindahl index (HI)	-0.06144	-0.01967	0.009138	-0.06366	-0.04637	-0.01037
	(0.08891)	(0.08379)	(0.08518)	(0.08876)	(0.08885)	(0.08490)
HI*Log (R&D int.)	0.5677**	4.7854***	2.9545	0.6506***	0.5412**	1.9335*
	(0.2260)	(1.5630)	(2.0095)	(0.2512)	(0.2600)	(1.1312)
Log (age + 1)	0.6063***	0.6002***	0.6026***	0.6055***	0.6071***	0.6009***
	(0.01628)	(0.01627)	(0.01628)	(0.01628)	(0.01627)	(0.01626)
Log (employment + 1)	0.2856***	0.2857***	0.2842***	0.2856***	0.2834***	0.2821***
	(0.01673)	(0.01672)	(0.01672)	(0.01673)	(0.01674)	(0.01670)
Log (employment + 1) sq.	-0.03790***	-0.03821***	-0.03801***	-0.03783***	-0.03753***	-0.03764***
	(0.002775)	(0.002775)	(0.002775)	(0.002775)	(0.002778)	(0.002772)

Log (live local unit + 1)	0.07864***	0.08312***	0.08258***	0.07676***	0.07752***	0.07940***
	(0.02006)	(0.02007)	(0.02006)	(0.02006)	(0.02006)	(0.02005)
Log (deflated turnover per employee + 1)	0.07158***	0.04819***	0.06247***	0.06876***	0.07714***	0.03536***
	(0.008224)	(0.007213)	(0.007711)	(0.008198)	(0.008313)	(0.007098)
Growth rate from t-1 to t	0.04101***	0.04240***	0.04067***	0.04042***	0.04218***	0.03736***
	(0.007968)	(0.007853)	(0.007925)	(0.007967)	(0.007990)	(0.007795)
Civil-only R&D firm	0.08347***	0.08792***	0.08189***	0.08436***	0.08648***	0.08022***
	(0.01626)	(0.01628)	(0.01624)	(0.01626)	(0.01627)	(0.01621)
Firm UK owned	0.007894	0.001999	0.007879	0.008896	0.01128	-0.003665
	(0.03202)	(0.03212)	(0.03190)	(0.03201)	(0.03200)	(0.03187)
Pavitt class 1	-0.1241	-0.07501	-0.1151	-0.1157	-0.1335	-0.08013
	(0.1033)	(0.1033)	(0.1038)	(0.1033)	(0.1036)	(0.1030)
Pavitt class 2	0.07856	0.07853	0.07947	0.08125	0.07531	0.08359
	(0.06558)	(0.06560)	(0.06581)	(0.06560)	(0.06564)	(0.06564)
Pavitt class 3	0.1383**	0.1653**	0.1476**	0.1427**	0.1282*	0.1679**
	(0.06922)	(0.06942)	(0.06987)	(0.06923)	(0.06970)	(0.06921)
Pavitt class 5	0.1429**	0.1322*	0.1337*	0.1447**	0.1402**	0.1329*
	(0.07005)	(0.07015)	(0.07018)	(0.07008)	(0.07009)	(0.07014)
Real eff. exchange rate	-0.04013***	-0.04044***	-0.04013***	-0.04024***	-0.04032***	-0.04077***
	(0.0008118)	(0.0008122)	(0.0008120)	(0.0008116)	(0.0008104)	(0.0008242)
Crisis dummy = 1 in 1998, 2001 and 2008	-0.2351***	-0.2381***	-0.2324***	-0.2346***	-0.2343***	-0.2347***
	(0.02106)	(0.02109)	(0.02105)	(0.02103)	(0.02107)	(0.02102)
Log (FTSE350)	1.5296***	1.4962***	1.5218***	1.5252***	1.5373***	1.4833***
	(0.05111)	(0.05075)	(0.05089)	(0.05114)	(0.05120)	(0.05073)
Constant	-8.6587***	-8.2281***	-8.5346***	-8.5951***	-8.7274***	-8.0093***
	(0.4961)	(0.4914)	(0.4926)	(0.4960)	(0.4965)	(0.4909)
2-digit industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Ln(Sigma)	-0.4168***	-0.4159***	-0.4165***	-0.4167***	-0.4170***	-0.4152***
	(0.009319)	(0.009310)	(0.009325)	(0.009318)	(0.009329)	(0.009308)
Observations	45483	45477	45539	45495	45474	45584
AIC	21208.8	21258.3	21239.1	21217.0	21183.8	21339.7
BIC	22098.8	22148.3	22129.2	22106.9	22073.7	22229.8
Number of subjects	13927	13924	13925	13928	13926	13935
Number of failure times	10091	10102	10088	10094	10074	10113
Log likelihood	-10502.4	-10527.2	-10517.5	-10506.5	-10489.9	-10567.8

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All firms born in 2000 and after. Observations in the top 1% of the R&D intensity distribution for each R&D category are excluded.

Then, we took into account the risk of simultaneity, whereby firm's observation of its survival prospect may affect its R&D effort and other choice variables such as employment. To address this simultaneity (reverse causality) problem, we re-estimated the model by taking one-year lags of all firm-specific covariates. Results in Table 4 indicate that the findings are robust - with notable exception of the Herfindahl-Hirschman index (concentration) which turns out to be negative and significant.

Table 4: R&D expenditures, source of funding and firm survival: Lagged estimation

	Total R&D	Extramural R&D	Capital R&D	Current R&D	Private R&D	Public R&D
Log (R&D intensity + 1)	0.2007*** (0.04713)	0.3258*** (0.09811)	0.4677*** (0.1279)	0.1842*** (0.04932)	0.2576*** (0.05046)	-0.03697 (0.09603)
Log (R&D intensity + 1) sq.	-0.02782** (0.01119)	-0.04559** (0.02221)	-0.09759** (0.04387)	-0.02414** (0.01188)	-0.03874*** (0.01272)	0.03100 (0.03189)
Herfindahl index (HI)	-0.2084** (0.09318)	-0.1789** (0.08859)	-0.1802** (0.08872)	-0.2100** (0.09277)	-0.1992** (0.09242)	-0.1921** (0.08974)
HI*Log (R&D int.)	0.2918* (0.1530)	-0.01609 (0.4923)	0.06865 (0.4622)	0.3221** (0.1566)	0.2372 (0.1538)	0.9844** (0.4386)
Log (age + 1)	0.3162*** (0.01858)	0.3158*** (0.01858)	0.3149*** (0.01861)	0.3167*** (0.01859)	0.3171*** (0.01853)	0.3147*** (0.01873)
Log (employment + 1)	0.2582*** (0.02293)	0.2527*** (0.02288)	0.2546*** (0.02291)	0.2563*** (0.02293)	0.2569*** (0.02289)	0.2523*** (0.02295)
Log (employment + 1) sq.	-0.02386*** (0.003249)	-0.02319*** (0.003246)	-0.02344*** (0.003251)	-0.02361*** (0.003250)	-0.02371*** (0.003244)	-0.02304*** (0.003253)
Log (live local unit + 1)	-0.02357 (0.02607)	-0.02620 (0.02614)	-0.02535 (0.02616)	-0.02481 (0.02608)	-0.02281 (0.02604)	-0.02798 (0.02622)
Log (deflated turnover per employee + 1)	0.1391*** (0.01109)	0.1165*** (0.009627)	0.1205*** (0.009938)	0.1364*** (0.01106)	0.1399*** (0.01094)	0.1133*** (0.01000)
Growth rate from t-1 to t	-0.004102 (0.007033)	-0.009820 (0.006939)	-0.008056 (0.007006)	-0.004573 (0.007028)	-0.003430 (0.007043)	-0.01166* (0.006949)
Civil-only R&D firm	0.04815*** (0.01419)	0.05062*** (0.01422)	0.05117*** (0.01420)	0.04924*** (0.01418)	0.04760*** (0.01416)	0.05262*** (0.01420)
Firm UK owned	0.1010*** (0.02954)	0.09330*** (0.02959)	0.09531*** (0.02958)	0.1012*** (0.02954)	0.1022*** (0.02949)	0.09080*** (0.02963)
Pavitt class 1	0.1397*** (0.04145)	0.1591*** (0.04129)	0.1593*** (0.04131)	0.1435*** (0.04144)	0.1394*** (0.04132)	0.1646*** (0.04144)
Pavitt class 2	0.2146*** (0.04169)	0.2172*** (0.04174)	0.2177*** (0.04179)	0.2143*** (0.04172)	0.2114*** (0.04166)	0.2165*** (0.04186)
Pavitt class 3	0.05476	0.06212	0.06216	0.05557	0.05343	0.06576

	(0.04774)	(0.04778)	(0.04785)	(0.04776)	(0.04771)	(0.04783)
Pavitt class 5	0.07832	0.07409	0.07420	0.07935	0.07978	0.07663
	(0.07521)	(0.07523)	(0.07531)	(0.07525)	(0.07514)	(0.07540)
Real effective exchange rate	-0.06605***	-0.06613***	-0.06620***	-0.06608***	-0.06607***	-0.06632***
	(0.001107)	(0.001108)	(0.001108)	(0.001107)	(0.001105)	(0.001112)
Crisis dummy = 1 in 1998, 2001 and 2008	-0.1216***	-0.1280***	-0.1248***	-0.1233***	-0.1212***	-0.1284***
	(0.008823)	(0.008842)	(0.008877)	(0.008827)	(0.008822)	(0.008856)
Log (FTSE350)	1.0166***	1.0047***	1.0096***	1.0134***	1.0219***	0.9999***
	(0.04127)	(0.04109)	(0.04118)	(0.04124)	(0.04126)	(0.04117)
Constant	-2.0051***	-1.7676***	-2.5343***	-2.7067***	-2.0407***	-2.3950***
	(0.3528)	(0.3461)	(0.4015)	(0.4047)	(0.3538)	(0.3965)
2-digit industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Ln(Sigma)	-0.3185***	-0.3172***	-0.3165***	-0.3181***	-0.3194***	-0.3154***
	(0.01076)	(0.01077)	(0.01077)	(0.01077)	(0.01077)	(0.01081)
Observations	127735	127697	127780	127720	127709	127813
AIC	34786.4	34855.8	34899.4	34802.5	34811.2	34876.8
BIC	35157.2	35226.5	35270.2	35173.3	35182.0	35247.7
Number of subjects	28607	28610	28615	28604	28598	28613
Number of failure times	27154	27170	27129	27144	27130	27131
Log likelihood	-17355.2	-17389.9	-17411.7	-17363.3	-17367.6	-17400.4

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All firms born in 1974 and after. Observations in the top 1% of the R&D intensity distribution for each R&D category are excluded.

Finally, we checked whether estimation results are robust to model specification by following a step-wise estimation routine. We first estimated the model with total R&D intensity and its square. We subsequently added firm-specific covariates followed by industry covariates and macroeconomic environment factors. We also experimented with 1-digit and 2-digit industry dummies. The results in Table 5 are consistent with the baseline model, with the exception of the most truncated version. In that version, which includes only R&D intensity, its square and industry dummies the non-monotonic relationship between R&D intensity and survival was still evident. However, the coefficients had opposite signs to the baseline model. This is to be expected as the bare model is mis-specified.[6]

[6] We estimated step-wise regressions for other R&D types in the baseline model. The results are similar. These results are available on request.

Table 5: R&D expenditures, source of funding and firm survival: Step-wise estimation

	(1)	(2)	(3)	(4)	(5)
Log (R&D intensity + 1)	-0.6367*** (0.06309)	0.4432*** (0.06993)	0.3899*** (0.07343)	0.2707*** (0.05748)	0.2729*** (0.05647)
Log (R&D intensity + 1) sq.	0.2441*** (0.03433)	-0.1403*** (0.03478)	-0.1772*** (0.03490)	-0.1398*** (0.02787)	-0.1434*** (0.02751)
Herfindahl index (HI)			0.1927* (0.1017)	-0.1072 (0.07739)	-0.04956 (0.08064)
Log (R&D int.)*HI			1.5057*** (0.2443)	0.6047*** (0.1711)	0.6100*** (0.1714)
Log (age + 1)		0.2143*** (0.01860)	0.2174*** (0.01865)	0.3966*** (0.01418)	0.4080*** (0.01413)
Log (employment + 1)		0.2849*** (0.02314)	0.2805*** (0.02310)	0.2542*** (0.01742)	0.2591*** (0.01759)
Log (employment + 1) sq.		-0.02578*** (0.003362)	-0.02529*** (0.003351)	-0.02777*** (0.002522)	-0.02824*** (0.002546)
Log (live local unit + 1)		-0.09246*** (0.02652)	-0.09677*** (0.02653)	0.03244 (0.02006)	0.02394 (0.02008)
Log (deflated turnover per employee + 1)		0.2052*** (0.01136)	0.2051*** (0.01137)	0.1063*** (0.008406)	0.1066*** (0.008413)
Growth rate from t-1 to t		-0.009088 (0.006722)	-0.005281 (0.006763)	0.01949*** (0.005245)	0.01987*** (0.005191)
Civil-only R&D firm		-0.05170*** (0.01437)	-0.04891*** (0.01402)	0.08540*** (0.01109)	0.09196*** (0.01071)
Firm UK owned		0.1402*** (0.03149)	0.1369*** (0.03151)	0.08183*** (0.02358)	0.08343*** (0.02326)
Pavitt class 1			0.008330 (0.04368)	0.1086*** (0.03310)	-0.02663 (0.1035)
Pavitt class 2			0.1612*** (0.04418)	0.1771*** (0.03327)	0.1979*** (0.06720)
Pavitt class 3			-0.01445 (0.05032)	0.03088 (0.03784)	0.05278 (0.06493)
Pavitt class 5			0.1193 (0.08201)	0.09081 (0.05972)	0.09868 (0.07729)
Real effective exchange rate				-0.06260*** (0.0007987)	-0.06145*** (0.0007983)
Crisis dummy = 1 in 1998, 2001 and 2008				-0.4850*** (0.006273)	-0.4741*** (0.006350)
Log (FTSE350)				1.1067***	1.0958***

				(0.02943)	(0.02948)
Constant	0.2982	-1.8928***	-2.0670***	-3.9136***	-3.5449***
	(0.2792)	(0.3496)	(0.3526)	(0.3845)	(0.3380)
1 or 2 digit industry dummies	1 digit	1 digit	1 digit	1 digit	2 digit
Ln(Sigma)	-0.01465**	-0.07707***	-0.07802***	-0.2997***	-0.3110***
	(0.005747)	(0.006293)	(0.006350)	(0.006297)	(0.006376)
Observations	170166	168843	168843	168843	168843
AIC	73919.4	70520.4	70377.0	58714.9	58216.2
BIC	74140.4	70821.5	70738.3	59106.3	59260.0
Number of subjects	37026	36836	36836	36836	36836
Number of failure times	40732	39990	39990	39990	39990
Log likelihood	-36937.7	-35230.2	-35152.5	-29318.4	-29004.1

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All firms born in 1974 and after. Observations in the top 1% of the total R&D intensity distribution are excluded

A few observations are in order now that we have presented the results from various robustness checks. First, we can reiterate the two conclusion we derived from the baseline estimations in Table 2 above: (i) the data lends support to hypotheses 2 and 3 that posit a quadratic relationship between R&D intensity and firm survival. This relationship follows an inverted-U pattern and remains robust to different types of R&D, with the exception of publicly-funded business R&D; and (ii) the data also lends support to hypothesis 1, which posits that R&D intensity is more likely to increase survival time in more concentrated industries and the effect of market concentration on survival is ambiguous.

Secondly, the estimated coefficients for R&D intensity and its square retain their signs, but their magnitudes differ between different estimations. Yet, the turning points are more or less the same as the baseline model – usually within the top quartile of the R&D intensity distribution for total, current and private R&D. The notable exception is publicly-funded R&D intensity, which does not remain significant in the robustness checks. However its interaction with market concentration remains significant and positive, indicating that publicly-funded R&D tends to increase survival time as the level of market concentration increases.

Third: estimates for the effects of other firm-level covariates such as age and size remain robust to sample selection and model specification. Age is positively related to survival whilst size has an inverted-U relationship with survival. These findings are in line with theoretical predictions in Hopenhayn (1992) and Ericson and Pakes (1995); and with empirical findings reported in (Geroski, 1995), Cefis and Marsili (2005), Doms et al (1995) and Disney et al (2000).

Fourth: our findings indicate that real turnover per employees (as a crude measure of productivity) has a positive effect on survival time; and the effect is consistent across estimations and samples. This is in line with theoretical predictions in Hopenhayn (1992) and Ericson and Pakes (1995); and with empirical findings in (Audretsch, 1991), Cefis and Marsili (2005), Mata et al (1995), and Agarwal (1997). Also, we find that the growth rate of firm output (measured as deflated turnover) has a positive and significant effect on survival time in contemporaneous estimations; but the growth rate in the preceding year has no effect. Our findings for the contemporaneous growth effect are in line with Audretsch (1991), Hopenhayn (1992) and Ericson and Pakes (1995). The lagged effect, however, is not tested in previous studies. Our finding indicates that growth performance in the previous year does not necessarily increase survival time as past growth is not a predictor of growth in the current year, when the firm has to decide about exit or persistence on the basis of its market opportunities.

Fifth: We find that two firm characteristics that may be specific to UK firms have consistent effects on survival - UK ownership and engagement in civil R&D only. In all estimations, firms that engage in civil R&D only have higher survival rates compared to those that engage solely or partly in defence-related R&D. We think that this is due to absolute and relative decline in defence expenditures in the UK. Since the end of the Cold War, UK defence R&D expenditures fell from £5 billion in 1989 to £2 billion in 2012 (constant prices). In addition, the gap between civil and defence R&D expenditures has widened in favour of the former from £10 to £22 billion over the same period (ONS, 2014). During this process, some of the firms engaged solely or partly in defence-related R&D may have exited due to reduced subsidies or lower demand for defence-related R&D or both. In addition, we also find largely consistent evidence indicating that UK firms tend to have higher survival rates compared to foreign-owned firms. We think that this may be due aggressive relocation decisions of foreign firms, which are usually subsidiaries of multinational corporations in search of optimal location.

The evidence on the survival of multi-plant firms is mixed. Multi-plant firms tend to have higher survival rates only in the estimation where we control for left truncation. In other estimations, the number of live local units is either insignificant or does not remain robust to model specification. This finding indicates that firms with larger numbers of local units may enjoy longer survival time only if the risk pool consists of firms born in the same year or thereafter. In contrast, when the risk pool consists of newly-born firms with a large number of local units and others that had survived with smaller or zero local units, the number of local units is not a significant determinant of survival time.

Sixth: Our findings concerning Pavitt technology classes indicates that firms in industries specialised in the supply of technology (Pavitt class 2) tend to have higher survival rates compared to firms in other classes and the supplier-dominated technology (Pavitt class 4). In contrast to findings from non-parametric estimations results in Figure 1 above, lower survival rates in the science-based technology class (Pavitt class 1) do not hold when the survival rates are conditioned on firm, industry and macroeconomic covariates.

Finally: Our findings indicate that the macroeconomic environment has significant effects on firm survival. Currency appreciation tends to reduce survival rates due to reduced international competitiveness. This is in line with Holmes et al. (2010) and Bhattacharjee et al. (2009), who report real appreciation has a negative effect on survival of small and medium-sized enterprises in Northern Ireland. It is also in line with simulations results reported by Goudie and Meeks (1991), who utilised a demand-driven Keynesian model and demonstrated that larger number of UK firms are liable to failure when the currency appreciates. Of other indicators of the macroeconomic environment, the FTSE-350 index is found to have a positive effect on survival time; and the effect is consistent across samples and model specifications. This is in line with Jensent et al. (2008), who report that an increase in the stock market index increases the survival time of Australian firms. Finally, we find that the survival rate is significantly lower in the first year of periodic crisis, including the East Asian crisis of 1998, the dot.com bubble of 2001, and the first full-year of the recent financial crisis in 2008.

5. Conclusions

The findings in this study add to the existing evidence base concerning the relationship between firm-, industry- and macro-level variables and firm survival. This is done by drawing on a rich dataset for UK firms from 1997-2012 and conducting a number of robustness checks. The findings from a log-normal survival model indicate that age is positively related to survival time whereas size has an inverted-U relationship with survival. Also, higher levels of firm productivity are associated with longer survival time; but the growth of firm output increases survival time only when the effect is estimated contemporaneously. Finally, macroeconomic indicators such as business cycles and real currency appreciation affects survival time – and the estimated effects are in line with the existing literature.

However, this study has also contributed to existing knowledge about the relationship between innovation and market structure on the one hand and firm survival on the other. We have demonstrated that it is more appropriate to model the relationship between innovation (proxied with R&D intensity) and survival as a quadratic relationship. The quadratic relationship is driven by three factors: (i) the initial level of market concentration; (ii) the quadratic relationship between the rate of innovation (creative destruction) and productivity in Schumpeterian models; and (iii) the increased risk associated with increased size of the R&D projects in stochastic models of firm dynamics. In this setting, market concentration on its own may not affect survival rates directly, but it is one of the factors that mediates the relationship between innovation intensity and survival.

Using UK data for 39,705 firms from 1997-2012, our findings indicate that the relationship between R&D intensity and survival has an *inverted-U* shape. As R&D intensity increases from low initial level, survival rates increase but at slower rates. After the turning point, higher levels of R&D intensity may reduce survival rates. These findings are robust to left truncation, control for simultaneity bias and step-wise estimations. They are also consistent between different R&D types – including total R&D, extramural R&D, intramural R&D (not reported here due to space constraints), privately-funded R&D and current or capital R&D intensities.

We also find that market concentration on its own does not have a significant effect on survival, with the exception of lagged estimations that control for simultaneity bias. This finding is compatible with the hypothesis that we tested in this study: the level of market concentration has an ambiguous effect on survival, but it has a positive effect when interacted with R&D intensity. Stateed differently, firms that increase their R&D intensities in relatively more concentrated market have better chance of survival compared to those that innovate in less concentrated markets. This finding suggests that a Schumpeterian effect is at work: innovation tends to pay off more if the firm already has some market power.

Our findings go some way towards explaining the varied and often conflicting findings reported on the relationship between innovation and firm entry/exit. The existing work, with the exception of Sharapov et al (2011), adopts a linear modelling approach. Hence, it is not surprising that some studies may report a positive relationship while others report a negative one. Such discrepancy may well be related to different levels of market concentration, different levels of initial R&D intensities, and different levels of risk associated with R&D projects. The mediating effects of such factors cannot be captured through linear estimations. Hence, they depict the part of the elephant they touch but not the full picture of the beast. Quadratic specifications go some way towards providing a less partial account of the relationship between innovation and survival.

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Appendix

Table A1: Summary statistics - variables in levels

Variable	Observations	Mean	Coefficient of variation	Skewness
Total R&D intensity	183105	0.158	2.387	5.619
Extramural R&D intensity	183105	0.009	3.367	8.348
Capital R&D intensity	183105	0.009	2.691	7.146
Current R&D intensity	183105	0.137	2.410	5.681
Private R&D intensity	183105	0.129	2.411	5.867
Public R&D intensity	183105	0.019	3.517	7.161
Total R&D intensity sq.	183105	0.167	6.258	12.688
Extramural R&D intensity sq.	183105	0.001	9.449	18.067
Capital R&D intensity sq.	183105	0.001	8.152	18.769
Current R&D intensity sq.	183105	0.129	6.329	12.827
Private R&D intensity sq.	183105	0.114	6.523	13.412
Public R&D intensity sq.	183105	0.005	8.104	14.781
Total R&D intensity*HI	183105	0.015	3.414	11.815
Extramural R&D intensity*HI	183105	0.001	4.723	16.636
Capital R&D intensity*HI	183105	0.001	3.893	20.302
Current R&D intensity*HI	183105	0.013	3.458	12.501
Private R&D intensity*HI	183105	0.012	3.481	13.634
Public R&D intensity*HI	183105	0.002	4.374	13.033
Age	183105	14.329	0.601	0.461
Size (employment)	183105	114.126	9.903	68.412
Size squared (employment)^2	183105	129×10^4	77.622	117.949
Live local unit (plants other than HQ)	183105	1.932	17.766	167.212
Deflated turnover per employee	182905	212.310	28.783	127.214
Growth of deflated turnover	170725	0.044	14.606	0.670
Civil dummy = 1 if firm engages in civil R&D only	183105	0.415	1.186	0.343
UK ownership dummy -- 1 if firm is UK owned	183105	0.882	0.366	-2.365
Herfindahl index (HI) measure of concentration	183105	0.098	1.092	3.095
Pavitt technology class 1 (science-based)	183105	0.352	1.356	0.618
Pavitt technology class 2 (specialised suppliers of technology))	183105	0.217	1.901	1.375
Pavitt technology class 3 (scale-intensive)	183105	0.094	3.105	2.783
Pavitt technology class 4 (supplier-dominated)	183105	0.273	1.633	1.021

Pavitt technology class 5 (others)	183105	0.064	3.817	3.555
Average effective real exchange rate	183105	92.463	0.101	-0.294
Crisis dummy = 1 if year-- 1998, 2001 and 2008	183105	0.153	2.356	1.931
FTSE 350 index	183105	2791.732	0.130	-0.392
Number of firms	39705			

Note: the sample consists of all firms born in 1974 or after; but it excludes firms in the top 1% of the R&D intensity distribution for each R&D category.

Table A2: Summary statistics - variables in logs

Variable	Observations	Mean	Coefficient of variation	Skewness
Log (Total R&D intensity + 1)	183105	0.118	1.782	3.454
Log (Extram. R&D intensity + 1)	183105	0.009	3.149	7.434
Log (Capital R&D intensity + 1)	183105	0.009	2.557	6.446
Log (Current R&D intensity + 1)	183105	0.105	1.832	3.600
Log (Private R&D intensity + 1)	183105	0.100	1.831	3.726
Log (Public R&D intensity + 1)	183105	0.017	3.198	6.051
Log (Total R&D intensity) squared	183105	0.058	3.854	7.067
Log (Extram. R&D intensity) sq.	183105	0.001	8.395	16.010
Log (Capital R&D intensity) sq.	183105	0.001	7.305	16.374
Log (Current R&D intensity) sq.	183105	0.048	4.010	7.372
Log (Private R&D intensity) sq.	183105	0.044	4.127	7.702
Log (Public R&D intensity) sq.	183105	0.003	6.836	12.127
Log(Total R&D intensity)*HI	183105	0.011	2.645	8.501
Log(Extramur. R&D intensity)*HI	183105	0.001	4.455	15.312
Log(Capital R&D intensity)*HI	183105	0.001	3.720	18.308
Log(Current R&D intensity)*HI	183105	0.010	2.711	8.964
Log(Private R&D intensity)*HI	183105	0.009	2.739	9.581
Log(Public R&D intensity)*HI	183105	0.002	4.019	11.578
Log(Age + 1)	183105	2.530	0.274	-0.797
Log(Employment + 1)	183105	2.853	0.600	0.584
Log(Employment) squared	183105	11.066	1.086	1.938
Log (Local plant + 1)	183105	0.643	0.894	2.266
Log (Deflated T/O per employee + 1)	182905	4.265	0.248	0.121
Growth of deflated turnover	170725	0.044	14.606	0.670
Civil dummy = 1 if firm engages in civil R&D only	183105	0.415	1.186	0.343
UK ownership dummy = 1 if firm is UK owned	183105	0.882	0.366	-2.365
Herfindahl index (HI)	183105	0.098	1.092	3.095
Pavitt technology class 1 (science-based)	183105	0.352	1.356	0.618
Pavitt technology class 2 (specialised suppliers of technology))	183105	0.217	1.901	1.375
Pavitt technology class 3 (scale-intensive)	183105	0.094	3.105	2.783
Pavitt technology class 4 (supplier-dominated)	183105	0.273	1.633	1.021
Pavitt technology class 5 (others)	183105	0.064	3.817	3.555
Average effective real exchange rate	183105	92.463	0.101	-0.294
Crisis dummy = 1 if year = 1998, 2001 and 2008	183105	0.153	2.356	1.931
Log (FTSE 350 index)	183105	7.926	0.017	-0.613
Number of firms	39705			

Note: the sample consists of all firms born in 1974 or after; but it excludes firms in the top 1% of the R&D intensity distribution for each R&D category.